H.R INSTITUTE OF TECHNOLOGY

MACHINE LEARNING

[RCA-661]

MASTER OF COMPUTER APPLICATIONS

[MCA]

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INDEX

SR NO.	CONTENT	SIGNATURE
1.	Introduction to Machine Learning	
2.	Working of Machine Learning	
3.	Need for Machine Learning	
4.	Importance of Machine Learning	
5.	Types of Machine Learning 1. Supervised Learning 2. Unsupervised Learning 3. Semi-supervised Learning	
6.	Supervised Learning : 1. Linear regression 2. Logistic regression 3. Decision trees 4. Random Forest Classifier 5. K-nearest neighbors 6. Naïve Bayes	
7.	Unsupervised Learning : 1. K-Mean clustering 2. Principal Component Analysis 3. Support Vector Machine	
8.	Semi-Supervised Learning	
9.	Reinforcement	

Introduction to Machine Learning:

In the real world, we are surrounded by humans who can learn everything from their experiences with their learning capability, and we have computers or machines which work on our instructions. But can a machine also learn from experiences or past data like a human does? So here comes the role of Machine Learning.

Machine Learning is said as a subset of artificial intelligence that is mainly concerned with the development of algorithms which allow a computer to learn from the data and past experiences on their own. The term machine learning was first introduced by Arthur Samuel in 1959. We can define it in a summarized way as:

“Machine learning enables a machine to automatically learn from data, improve performance from experiences, and predict things without being explicitly programmed.”

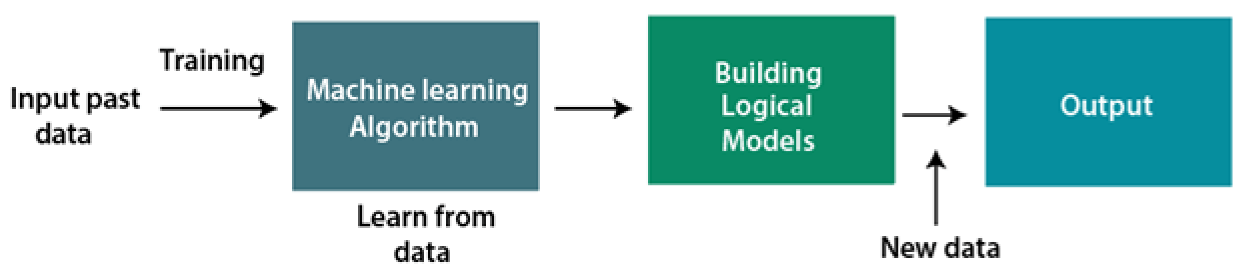
With the help of sample historical data, which is known as training data, machine learning algorithms build a mathematical model that helps in making predictions or decisions without being explicitly programmed. Machine learning brings computer science and statistics together for creating predictive models. Machine learning constructs or uses the algorithms that learn from historical data. The more we will provide the information, the higher will be the performance.

A machine has the ability to learn if it can improve its performance by gaining more data.

Working of Machine Learning:

A Machine Learning system learns from historical data, builds the prediction models, and whenever it receives new data, predicts the output for it. The accuracy of predicted output depends upon the amount of data, as the huge amount of data helps to build a better model which predicts the output more accurately.

Suppose we have a complex problem, where we need to perform some predictions, so instead of writing a code for it, we just need to feed the data to generic algorithms, and with the help of these algorithms, machine builds the logic as per the data and predict the output. Machine learning has changed our way of thinking about the problem. The below block diagram explains the working of Machine Learning algorithm:



Features of Machine Learning:

- Machine learning uses data to detect various patterns in a given dataset.
- It can learn from past data and improve automatically.
- It is a data-driven technology.
- Machine learning is much similar to data mining as it also deals with the huge amount of the data.

Need for Machine Learning :

The need for machine learning is increasing day by day. The reason behind the need for machine learning is that it is capable of doing tasks that are too complex for a person to implement directly. As a human, we have some limitations as we cannot access the huge amount of data manually, so for this, we need some computer systems and here comes the machine learning to make things easy for us.

We can train machine learning algorithms by providing them the huge amount of data and let them explore the data, construct the models, and predict the required output automatically. The performance of the machine learning algorithm depends on the amount of data, and it can be determined by the cost function. With the help of machine learning, we can save both time and money.

The importance of machine learning can be easily understood by its uses cases, Currently, machine learning is used in self-driving cars, cyber fraud detection, face recognition, and friend suggestion by Facebook, etc. Various top companies such as Netflix and Amazon have build machine learning models that are using a vast amount of data to analyze the user interest and recommend product accordingly.

Following are some key points which show the importance of Machine Learning:

- Rapid increment in the production of data
- Solving complex problems, which are difficult for a human
- Decision making in various sector including finance
- Finding hidden patterns and extracting useful information from data.

Importance of Machine Learning :

Machine learning has several very practical applications that drive the kind of real business results – such as time and money savings – that have the potential to dramatically impact the future of your organization. At Interactions in particular, we see tremendous impact occurring within the customer care industry, whereby machine learning is allowing people to get things done more quickly and efficiently. Through Virtual Assistant solutions, machine learning automates tasks that would otherwise need to be performed by a live agent – such as changing a password or checking an account balance. This frees up valuable agent time that can be used to focus on the kind of customer care that humans perform best: high touch, complicated decision-making that is not as easily handled by a machine. At Interactions, we further improve the process by eliminating the decision of whether a request should be sent to a human or a machine: unique Adaptive Understanding technology, the machine learns to be aware of its limitations, and bail out to humans when it has a low confidence in providing the correct solution.

Data is the lifeblood of all business. Data-driven decisions increasingly make the difference between keeping up with competition or falling further behind. Machine learning can be the key to unlocking the value of corporate and customer data and enacting decisions that keep a company ahead of the competition.

Machine learning has made dramatic improvements in the past few years, but we are still very far from reaching human performance. Many times, the machine needs the assistance of human to complete its task. At Interactions, we have deployed Virtual Assistant solutions that seamlessly blend artificial with true human intelligence to deliver the highest level of accuracy and understanding.

Resurging interest in machine learning is due to the same factors that have made data mining and Bayesian analysis more popular than ever. Things like growing volumes and varieties of available data, computational processing that is cheaper and more powerful, and affordable data storage.

All of these things mean it's possible to quickly and automatically produce models that can analyze bigger, more complex data and deliver faster, more accurate results – even on a very large scale. And by building precise models, an organization has a better chance of identifying profitable opportunities – or avoiding unknown risks.

Machine learning as technology helps analyze large chunks of data, easing the tasks of data scientists in an automated process and is gaining a lot of prominence and recognition. Machine learning has changed the way data extraction and interpretation works by involving automatic sets of generic methods that have replaced traditional statistical techniques.

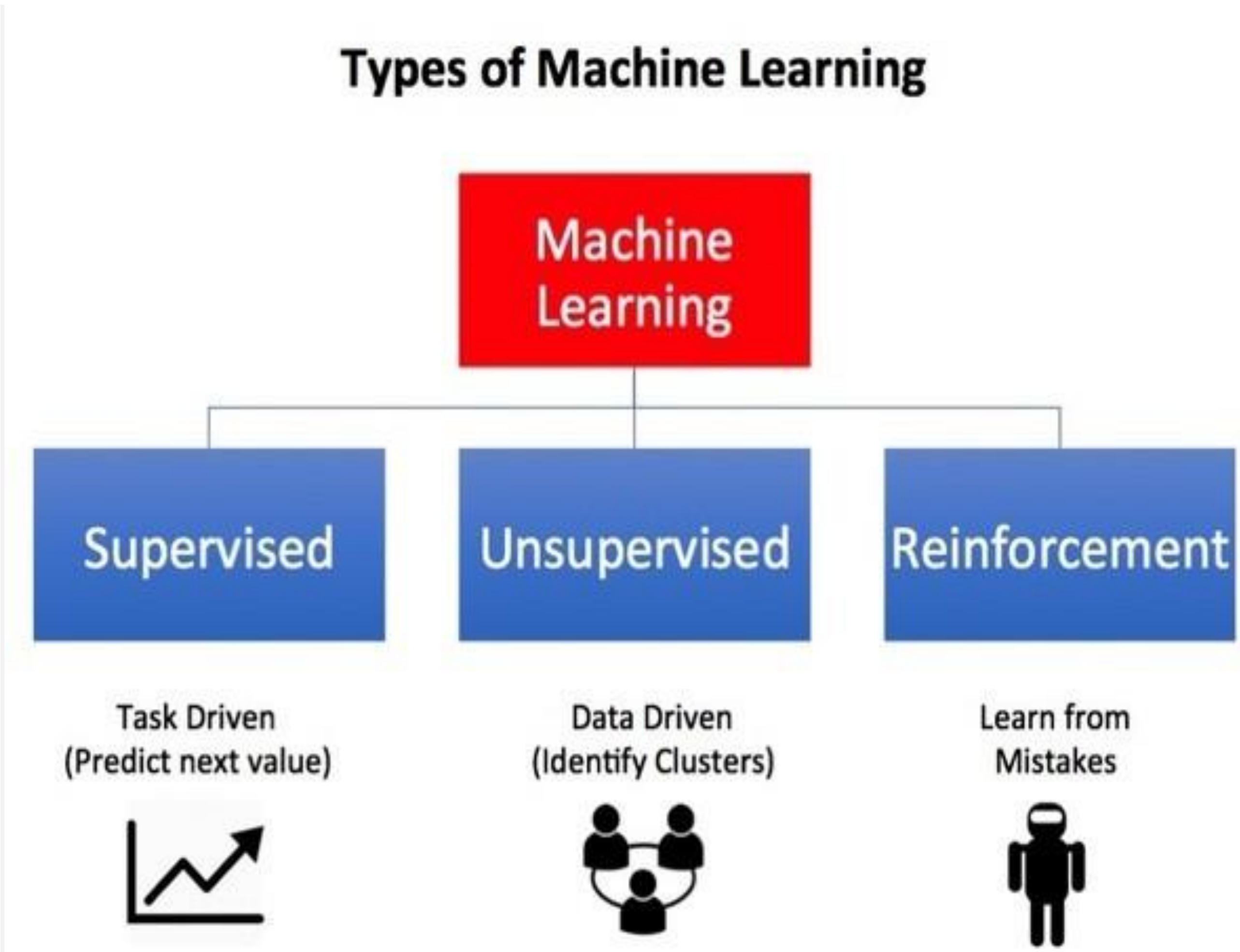
Machine Learning Use Cases :

Machine learning has applications in all types of industries, including manufacturing, retail, healthcare and life sciences, travel and hospitality, financial services, and energy, feedstock, and utilities. Use cases include:

- **Manufacturing.** Predictive maintenance and condition monitoring
- **Retail.** Upselling and cross-channel marketing
- **Healthcare and life sciences.** Disease identification and risk satisfaction
- **Travel and hospitality.** Dynamic pricing
- **Financial services.** Risk analytics and regulation
- **Energy.** Energy demand and supply optimization

Types of Machine Learning :

At a high-level, machine learning is simply the study of teaching a computer program or algorithm how to progressively improve upon a set task that it is given. On the research-side of things, machine learning can be viewed through the lens of theoretical and mathematical modeling of how this process works. However, more practically it is the study of how to build applications that exhibit this iterative improvement. There are many ways to frame this idea, but largely there are three major recognized categories: supervised learning, unsupervised learning, and reinforcement learning.



Supervised Learning :

In supervised learning, we use known or labeled data for the training data. Since the data is known, the learning is, therefore, supervised, i.e., directed into successful execution. The input data goes through the Machine Learning algorithm and is used to train the model. Once the model is trained based on the known data, you can use unknown data into the model and get a new response.

Supervised learning is the most popular paradigm for machine learning. It is the easiest to understand and the simplest to implement. It is very similar to teaching a child with the use of flash cards.

Given data in the form of examples with labels, we can feed a learning algorithm these example-label pairs one by one, allowing the algorithm to predict the label for each example, and giving it feedback as to whether it predicted the right answer or not. Over time, the algorithm will learn to approximate the exact nature of the relationship between examples and their labels.

The top algorithms currently being used for supervised learning are:

- Random forest
- Linear regression
- Logistic regression
- Decision trees
- K-nearest neighbors
- Naive Bayes

1. LINEAR REGRESSION:

Linear regression may be defined as the statistical model that analyzes the linear relationship between a dependent variable with given set of independent variables. Linear relationship between variables means that when the value of one or more independent variables will change (increase or decrease), the value of dependent variable will also change accordingly (increase or decrease).

Mathematically the relationship can be represented with the help of following equation −

Y=mX+bY=mX+b

Here, Y is the dependent variable we are trying to predict.

X is the independent variable we are using to make predictions.

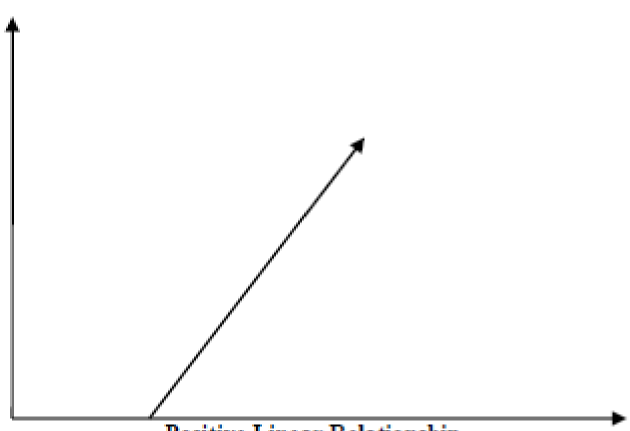
m is the slop of the regression line which represents the effect X has on Y

b is a constant, known as the YY-intercept. If X = 0,Y would be equal to bb.

Furthermore, the linear relationship can be positive or negative in nature as explained below −

Positive Linear Relationship

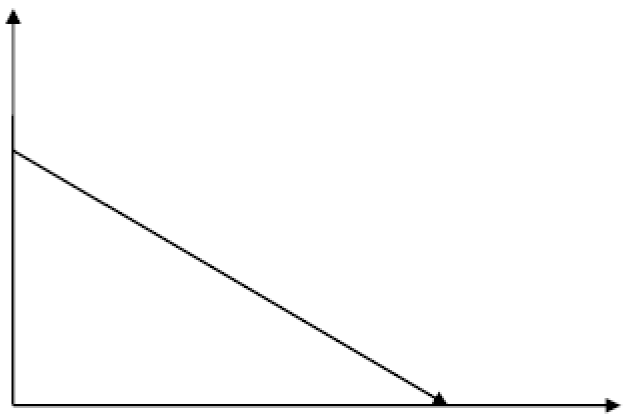
A linear relationship will be called positive if both independent and dependent variable increases. It can be understood with the help of following graph −



Positive Linear Relationship

Negative Linear relationship

A linear relationship will be called positive if independent increases and dependent variable decreases. It can be understood with the help of following graph −



Negative Linear Relationship

Types of Linear Regression:

Linear regression is of the following two types −

- Simple Linear Regression
- Multiple Linear Regression

Assumptions:

The following are some assumptions about dataset that is made by Linear Regression model –

- **Multi-collinearity** − Linear regression model assumes that there is very little or no multi-collinearity in the data. Basically, multi-collinearity occurs when the independent variables or features have dependency in them.
- **Auto-correlation** − Another assumption Linear regression model assumes is that there is very little or no auto-correlation in the data. Basically, auto-correlation occurs when there is dependency between residual errors.
- **Relationship between variables** − Linear regression model assumes that the relationship between response and feature variables must be linear.

2. LOGISTIC REGRESSION :

Logistic regression is a statistical method for predicting binary classes. The outcome or target variable is dichotomous in nature. Dichotomous means there are only two possible classes. For example, it can be used for cancer detection problems. It computes the probability of an event occurrence.

It is a special case of linear regression where the target variable is categorical in nature. It uses a log of odds as the dependent variable. Logistic Regression predicts the probability of occurrence of a binary event utilizing a logit function.

Logistic regression is a supervised learning classification algorithm used to predict the probability of a target variable. The nature of target or dependent variable is dichotomous, which means there would be only two possible classes.

In simple words, the dependent variable is binary in nature having data coded as either 1 (stands for success/yes) or 0 (stands for failure/no).

Types of Logistic Regression :

Generally, logistic regression means binary logistic regression having binary target variables, but there can be two more categories of target variables that can be predicted by it. Based on those number of categories, Logistic regression can be divided into following types −

Binary or Binomial

In such a kind of classification, a dependent variable will have only two possible types either 1 and 0. For example, these variables may represent success or failure, yes or no, win or loss etc.

Multinomial :

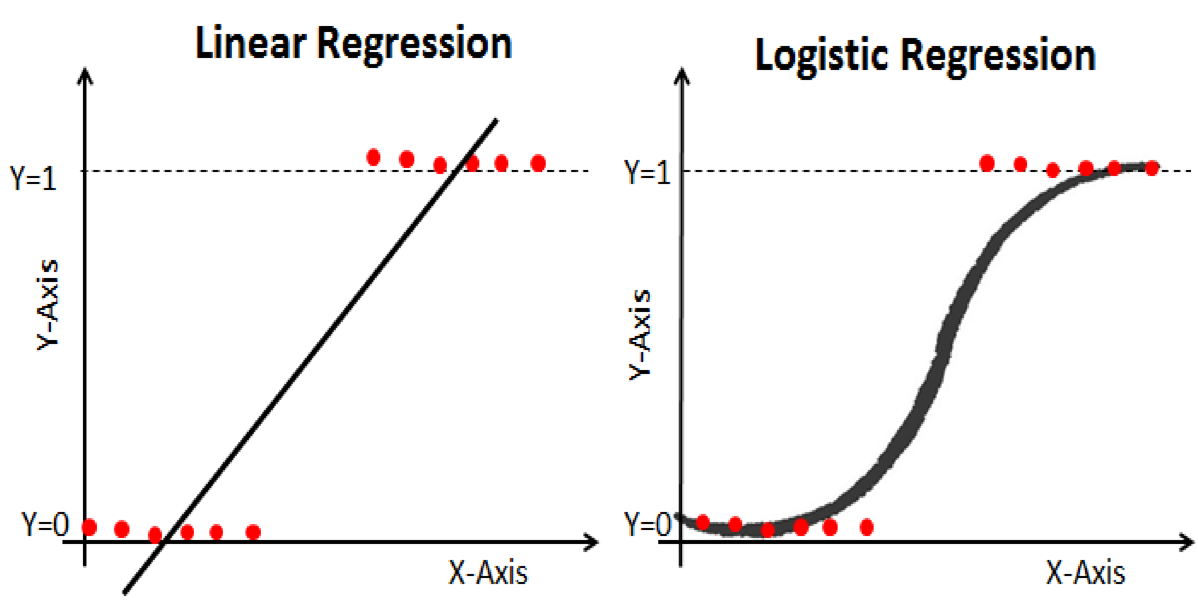
In such a kind of classification, dependent variable can have 3 or more possible ***unordered*** types or the types having no quantitative significance. For example, these variables may represent “Type A” or “Type B” or “Type C”.

Properties of Logistic Regression:

- The dependent variable in logistic regression follows Bernoulli Distribution.
- Estimation is done through maximum likelihood.
- No R Square, Model fitness is calculated through Concordance, KS-Statistics.

Linear Regression Vs. Logistic Regression :

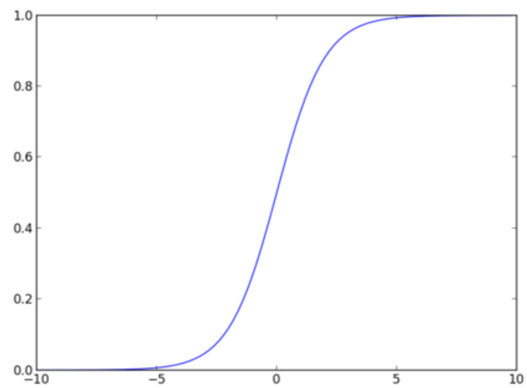
Linear regression gives you a continuous output, but logistic regression provides a constant output. An example of the continuous output is house price and stock price. Example's of the discrete output is predicting whether a patient has cancer or not, predicting whether the customer will churn. Linear regression is estimated using Ordinary Least Squares (OLS) while logistic regression is estimated using Maximum Likelihood Estimation (MLE) approach.



Sigmoid Function :

The sigmoid function, also called logistic function gives an ‘S’ shaped curve that can take any real-valued number and map it into a value between 0 and 1. If the curve goes to positive infinity, y predicted will become 1, and if the curve goes to negative infinity, y predicted will become 0. If the output of the sigmoid function is more than 0.5, we can classify the outcome as 1 or YES, and if it is less than 0.5, we can classify it as 0 or NO. The outputcannotFor example: If the output is 0.75, we can say in terms of probability as: There is a 75 percent chance that patient will suffer from cancer.

$$f(x) = \frac{1}{1 + e^{-(x)}}$$



Logistic Regression Assumptions :

Before diving into the implementation of logistic regression, we must be aware of the following assumptions about the same −

- In case of binary logistic regression, the target variables must be binary always and the desired outcome is represented by the factor level 1.
- There should not be any multi-collinearity in the model, which means the independent variables must be independent of each other.
- We must include meaningful variables in our model.
- We should choose a large sample size for logistic regression.

3. Decision Tree Algorithm:

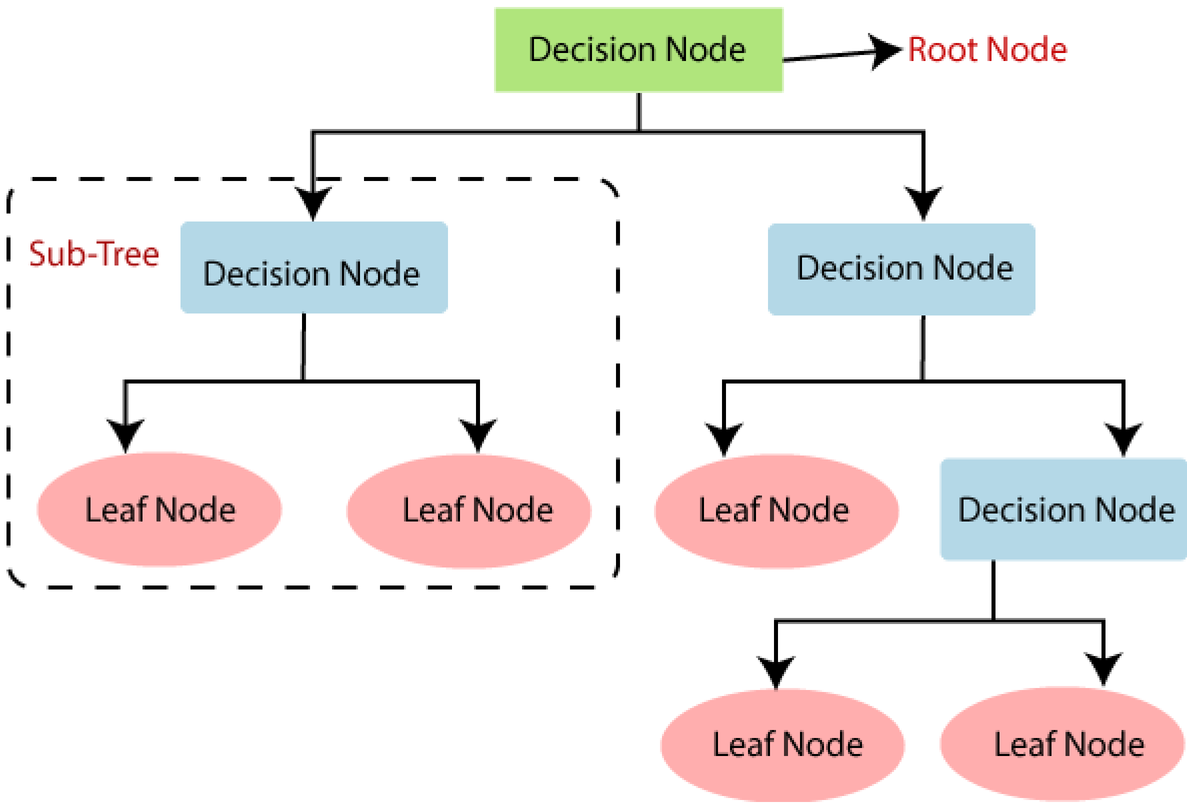
A Decision Tree is a Supervised Machine Learning algorithm which looks like an inverted tree, wherein each node represents a predictor variable (feature), the link between the nodes represents a Decision and each leaf node represents an outcome (response variable).

- Decision Tree is a Supervised learning technique that can be used for both classification and Regression problems, but mostly it is preferred for solving Classification problems. It is a tree-structured classifier, where internal nodes represent the features of a dataset, branches represent the decision rules and each leaf node represents the outcome.
- In a Decision tree, there are two nodes, which are the Decision Node and Leaf Node. Decision nodes are used to make any decision and have multiple branches, whereas Leaf nodes are the output of those decisions and do not contain any further branches.
- It is a graphical representation for getting all the possible solutions to a problem/decision based on given conditions.
- It is called a decision tree because, similar to a tree, it starts with the root node, which expands on further branches and constructs a tree-like structure.
- A decision tree simply asks a question, and based on the answer (Yes/No), it further split the tree into subtrees.

We have the following two types of decision trees.

a) **Classification decision trees** − In this kind of decision trees, the decision variable is categorical. The above decision tree is an example of classification decision tree.
b) **Regression decision trees** − In this kind of decision trees, the decision variable is continuous.

Below diagram explains the general structure of a decision tree:



Why use Decision Trees?

There are various algorithms in Machine learning, so choosing the best algorithm for the given dataset and problem is the main point to remember while creating a machine learning model. Below are the two reasons for using the Decision tree:

- Decision Trees usually mimic human thinking ability while making a decision, so it is easy to understand.
- The logic behind the decision tree can be easily understood because it shows a tree-like structure.

How does the Decision Tree algorithm Work?

In a decision tree, for predicting the class of the given dataset, the algorithm starts from the root node of the tree. This algorithm compares the values of root attribute with the record (real dataset) attribute and, based on the comparison, follows the branch and jumps to the next node.

For the next node, the algorithm again compares the attribute value with the other sub-nodes and move further. It continues the process until it reaches the leaf node of the tree. The complete process can be better understood using the below algorithm:

Step-1: Begin the tree with the root node, says S, which contains the complete dataset.

Step-2: Find the best attribute in the dataset using Attribute Selection Measure (ASM).

Step-3: Divide the S into subsets that contains possible values for the best attributes.

Step-4: Generate the decision tree node, which contains the best attribute.

Step-5: Recursively make new decision trees using the subsets of the dataset created in step -3. Continue this process until a stage is reached where you cannot further classify the nodes and called the final node as a leaf node.

4. RANDOM FOREST ALGORITHM :

Random forest is a supervised learning algorithm which is used for both classification as well as regression. But however, it is mainly used for classification problems. As we know that a forest is made up of trees and more trees means more robust forest. Similarly, random forest algorithm creates decision trees on data samples and then gets the prediction from each of them and finally selects the best solution by means of voting. It is an ensemble method which is better than a single decision tree because it reduces the over-fitting by averaging the result.

First, Random Forest algorithm is a supervised classification algorithm. We can see it from its name, which is to create a forest by some way and make it random. There is a direct relationship between the number of trees in the forest and the results it can get: the larger the number of trees, the more accurate the result.

The difference between Random Forest algorithm and the decision tree algorithm is that in Random Forest, the process es of finding the root node and splitting the feature nodes will run randomly.

Working of Random Forest Algorithm :

We can understand the working of Random Forest algorithm with the help of following steps −

Step 1 − First, start with the selection of random samples from a given dataset.

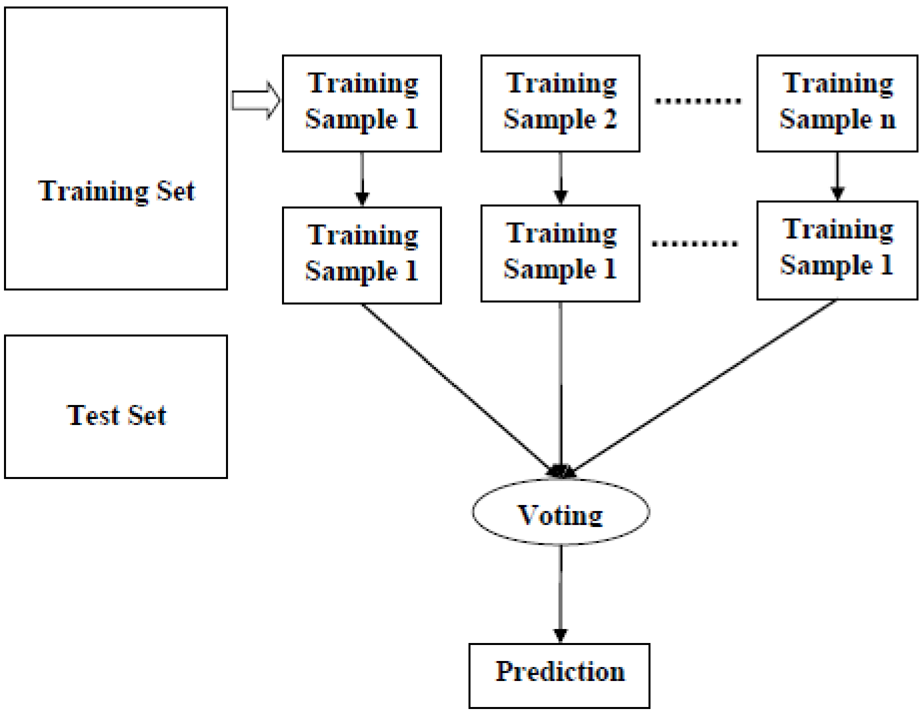
Step 2 − Next, this algorithm will construct a decision tree for every sample. Then it will get the prediction result from every decision tree.

Step 3 − In this step, voting will be performed for every predicted result.

Step 4 − At last, select the most voted prediction result as the final prediction result.

The following diagram will illustrate its working –

Random Forest Algorithm



Why Random Forest algorithm?

The author gives four advantages to illustrate why we use Random Forest algorithm. The one mentioned repeatedly by the author is that it can be used for both classification and regression tasks.

Overfitting is one critical problem that may make the results worse, but for Random Forest algorithm, if there are enough trees in the forest, the classifier won't overfit the model.

The third advantage is the classifier of Random Forest can handle missing values, and the last advantage is that the Random Forest classifier can be modeled for categorical values.

How Random Forest algorithm works?

There are two stages in Random Forest algorithm, one is random forest creation, the other is to make a prediction from the random forest classifier created in the first stage. The whole process is shown below, and it's easy to understand using the figure.

Here the author firstly shows the Random Forest creation pseudocode:

1. Randomly select "K" features from total "m" features where k << m
2. Among the "K" features, calculate the node "d" using the best split point
3. Split the node into daughter nodes using the best split
4. Repeat the a to c steps until "l" number of nodes has been reached
5. Build forest by repeating steps a to d for "n" number times to create "n" number of trees

In the next stage, with the random forest classifier created, we will make the prediction. The random forest prediction pseudocode is shown below:

- Takes the **test features** and use the rules of each randomly created decision tree to predict the outcome and stores the predicted outcome (target)
- Calculate the **votes** for each predicted target
- Consider the **high voted** predicted target as the **final prediction** from the random forest algorithm

5. K- NEAREST NEIGHBORS :

K-nearest neighbors (KNN) algorithm is a type of supervised ML algorithm which can be used for both classification as well as regression predictive problems. However, it is mainly used for classification predictive problems in industry.

- K-Nearest Neighbour is one of the simplest Machine Learning algorithms based on Supervised Learning technique.
- K-NN algorithm assumes the similarity between the new case/data and available cases and put the new case into the category that is most similar to the available categories.
- K-NN algorithm stores all the available data and classifies a new data point based on the similarity. This means when new data appears then it can be easily classified into a well suite category by using K- NN algorithm.
- K-NN algorithm can be used for Regression as well as for Classification but mostly it is used for the Classification problems.
- It is also called a lazy learner algorithm because it does not learn from the training set immediately instead it stores the dataset and at the time of classification, it performs an action on the dataset.
- KNN algorithm at the training phase just stores the dataset and when it gets new data, then it classifies that data into a category that is much similar to the new data.

Example:

Suppose, we have an image of a creature that looks similar to cat and dog, but we want to know either it is a cat or dog. So for this identification, we can use the KNN algorithm, as it works on a similarity measure. Our KNN model will find the similar features of the new data set to the cats and dogs images and based on the most similar features it will put it in either cat or dog category.

Working of knn:

K-nearest neighbors (KNN) algorithm uses 'feature similarity' to predict the values of new datapoints which further means that the new data point will be assigned a value based on how closely it matches the points in the training set. We can understand its working with the help of following steps

Step 1 − For implementing any algorithm, we need dataset. So during the first step of KNN, we must load the training as well as test data.

Step 2 − Next, we need to choose the value of K i.e. the nearest data points. K can be any integer.

Step 3 − For each point in the test data do the following −

3.1 − Calculate the distance between test data and each row of training data with the help of any of the method namely: Euclidean, Manhattan or Hamming distance. The most commonly used method to calculate distance is Euclidean.

3.2 − Now, based on the distance value, sort them in ascending order.

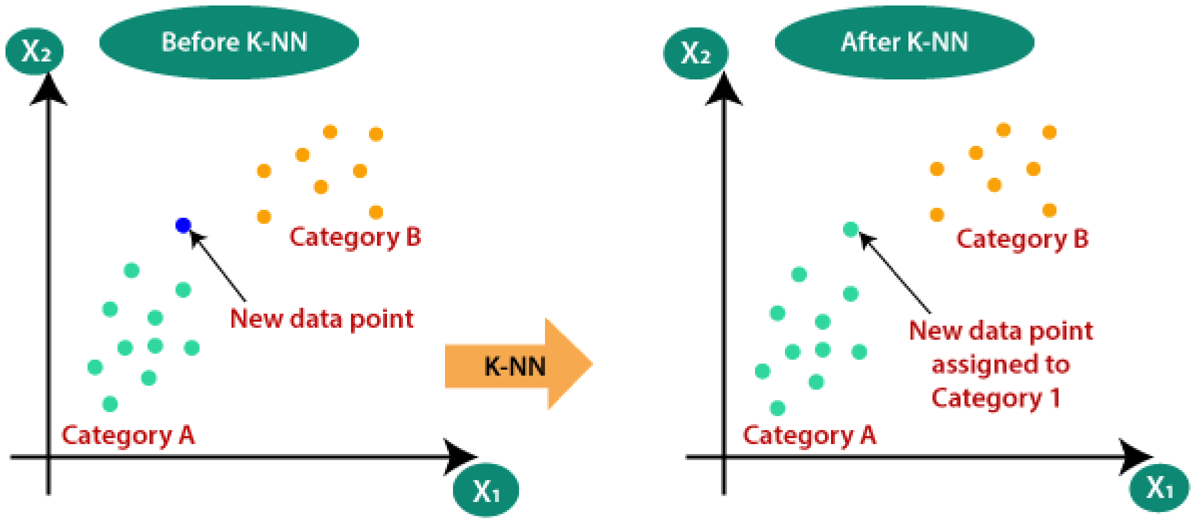
3.3 − Next, it will choose the top K rows from the sorted array.

3.4 − Now, it will assign a class to the test point based on most frequent class of these rows.

Step 4 − End

Why do we need a K-NN Algorithm?

Suppose there are two categories, i.e., Category A and Category B, and we have a new data point x1, so this data point will lie in which of these categories. To solve this type of problem, we need a K-NN algorithm. With the help of K-NN, we can easily identify the category or class of a particular dataset. Consider the below diagram:



Firstly, we will choose the number of neighbors, so we will choose the k=5.

Next, we will calculate the Euclidean distance between the data points. The Euclidean distance is the distance between two points, which we have already studied in geometry.

K-Nearest Neighbor(KNN) Algorithm for Machine Learning

By calculating the Euclidean distance we got the nearest neighbors, as three nearest neighbors in category A and two nearest neighbors in category B.

Advantages of KNN Algorithm:

- It is simple to implement.
- It is robust to the noisy training data
- It can be more effective if the training data is large.

Disadvantages of KNN Algorithm:

- Always needs to determine the value of K which may be complex some time.
- The computation cost is high because of calculating the distance between the data points for all the training samples.

6. Naïve Bayes Classifier Algorithm:

Naive Bayes is a probabilistic technique for constructing classifiers. The characteristic assumption of the naive Bayes classifier is to consider that the value of a particular feature is independent of the value of any other feature, given the class variable.

Despite the oversimplified assumptions mentioned previously, naive Bayes classifiers have good results in complex real-world situations. An advantage of naive Bayes is that it only requires a small amount of training data to estimate the parameters necessary for classification and that the classifier can be trained incrementally.

- Naïve Bayes algorithm is a supervised learning algorithm, which is based on Bayes theorem and used for solving classification problems.
- It is mainly used in text classification that includes a high-dimensional training dataset.
- Naïve Bayes Classifier is one of the simple and most effective Classification algorithms which helps in building the fast machine learning models that can make quick predictions.
- It is a probabilistic classifier, which means it predicts on the basis of the probability of an object.

Naive Bayes is a conditional probability model: given a problem instance to be classified, represented by a vector $x = (x1, \ldots, xn)$ representing some n features (independent variables), it assigns to this instance probabilities for each of K possible outcomes or classes.

$$p(Ck|x1,.....,xn)$$

The problem with the above formulation is that if the number of features n is large or if a feature can take on a large number of values, then basing such a model on probability tables is infeasible. We therefore reformulate the model to make it simpler. Using Bayes theorem, the conditional probability can be decomposed as − $p(Ck|x)=p(Ck)p(x|Ck)p(x)$

Why is it called Naïve Bayes?

The Naïve Bayes algorithm is comprised of two words Naïve and Bayes, Which can be described as:

Naïve: It is called Naïve because it assumes that the occurrence of a certain feature is independent of the occurrence of other features. Such as if the fruit is identified on the bases of color, shape, and taste, then red, spherical, and sweet fruit is recognized as an apple. Hence each feature individually contributes to identify that it is an apple without depending on each other.

Bayes: It is called Bayes because it depends on the principle of Bayes' Theorem.

Bayes' Theorem:

Bayes' theorem is also known as Bayes' Rule or Bayes' law, which is used to determine the probability of a hypothesis with prior knowledge. It depends on the conditional probability.

The formula for Bayes' theorem is given as:

Naïve Bayes Classifier Algorithm:

$$P(A|B)=\frac{P(B|A)P(A)}{P(B)}$$

Where,

P(A|B) is Posterior probability: Probability of hypothesis A on the observed event B.

P(B|A) is Likelihood probability: Probability of the evidence given that the probability of a hypothesis is true.

P(A) is Prior Probability: Probability of hypothesis before observing the evidence.

P(B) is Marginal Probability: Probability of Evidence.

Working of Naïve Bayes' Classifier:

Working of Naïve Bayes' Classifier can be understood with the help of the below example:

Suppose we have a dataset of weather conditions and corresponding target variable "Play". So using this dataset we need to decide that whether we should play or not on a particular day according to the weather conditions. So to solve this problem, we need to follow the below steps:

1. Convert the given dataset into frequency tables.
2. Generate Likelihood table by finding the probabilities of given features.
3. Now, use Bayes theorem to calculate the posterior probability.

Advantages of Naïve Bayes Classifier:

- Naïve Bayes is one of the fast and easy ML algorithms to predict a class of datasets.
- It can be used for Binary as well as Multi-class Classifications.
- It performs well in Multi-class predictions as compared to the other Algorithms.
- It is the most popular choice for text classification problems.

Disadvantages of Naïve Bayes Classifier:

- Naive Bayes assumes that all features are independent or unrelated, so it cannot learn the relationship between features.

Applications of Naïve Bayes Classifier:

- It is used for Credit Scoring.
- It is used in medical data classification.
- It can be used in real-time predictions because Naïve Bayes Classifier is an eager learner.
- It is used in Text classification such as Spam filtering and Sentiment analysis.

Types of Naïve Bayes Model:

There are three types of Naive Bayes Model, which are given below:

- **Gaussian:** The Gaussian model assumes that features follow a normal distribution. This means if predictors take continuous values instead of discrete, then the model assumes that these values are sampled from the Gaussian distribution.

- **Multinomial:** The Multinomial Naïve Bayes classifier is used when the data is multinomial distributed. It is primarily used for document classification problems, it means a particular document belongs to which category such as Sports, Politics, education, etc.
  The classifier uses the frequency of words for the predictors.

- **Bernoulli:** The Bernoulli classifier works similar to the Multinomial classifier, but the predictor variables are the independent Booleans variables. Such as if a particular word is present or not in a document. This model is also famous for document classification tasks.

Python Implementation of the Naïve Bayes algorithm:

Now we will implement a Naive Bayes Algorithm using Python. So for this, we will use the "user_data" dataset, which we have used in our other classification model. Therefore we can easily compare the Naive Bayes model with the other models.

Steps to implement:

- Data Pre-processing step
- Fitting Naive Bayes to the Training set
- Predicting the test result
- Test accuracy of the result(Creation of Confusion matrix)
- Visualizing the test set result.

Unsupervised Learning :

In unsupervised learning, the training data is unknown and unlabeled - meaning that no one has looked at the data before. Without the aspect of known data, the input cannot be guided to the algorithm, which is where the unsupervised term originates from. This data is fed to the Machine Learning algorithm and is used to train the model. The trained model tries to search for a pattern and give the desired response. In this case, it is often like the algorithm is trying to break code like the Enigma machine but without the human mind directly involved but rather a machine.

In this case, the unknown data consists of apples and pears which look similar to each other. The trained model tries to put them all together so that you get the same things in similar groups.

In some pattern recognition problems, the training data consists of a set of input vectors x without any corresponding target values. The goal in such unsupervised learning problems may be to discover groups of similar examples within the data, where it is called clustering, or to determine how the data is distributed in the space, known as density estimation. To put forward in simpler terms, for a n-sampled space x1 to xn, true class labels are not provided for each sample, hence known as learning without teacher.

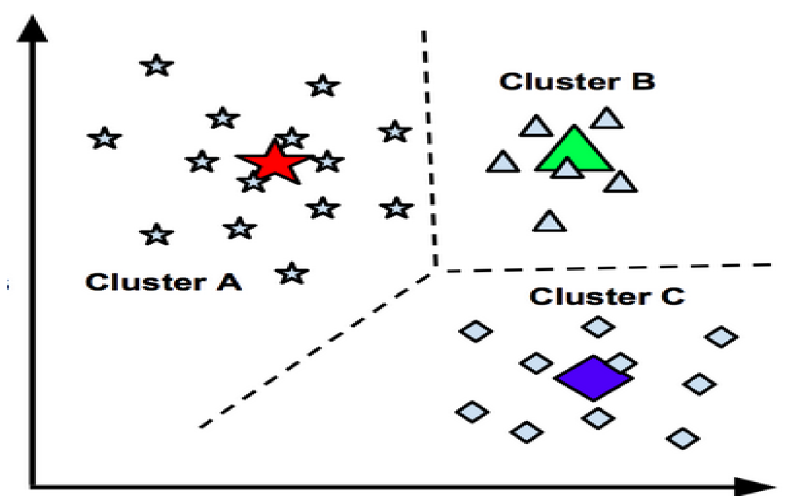
The top algorithms currently being used for unsupervised learning are:

- Partial least squares
- Fuzzy means
- Singular value decomposition
- K-means clustering
- Apriori
- Hierarchical clustering
- Principal component analysis

1.K-Means Clustering :

K-means clustering algorithm computes the centroids and iterates until we it finds optimal centroid. It assumes that the number of clusters are already known. It is also called flat clustering algorithm. The number of clusters identified from data by algorithm is represented by 'K' in K-means.

- In this algorithm, the data points are assigned to a cluster in such a manner that the sum of the squared distance between the data points and centroid would be minimum. It is to be understood that less variation within the clusters will lead to more similar data points within same cluster.
- K-means clustering is one of the simplest and popular unsupervised machine learning algorithms.
- Typically, unsupervised algorithms make inferences from datasets using only input vectors without referring to known, or labelled, outcomes.
- AndreyBu, who has more than 5 years of machine learning experience and currently teaches people his skills, says that "the objective of K-means is simple: group similar data points together and discover underlying patterns. To achieve this objective, K-means looks for a fixed number (k) of clusters in a dataset."
- You'll define a target number k, which refers to the number of centroids you need in the dataset. A centroid is the imaginary or real location representing the center of the cluster.
- Every data point is allocated to each of the clusters through reducing the in-cluster sum of squares.
- A cluster refers to a collection of data points aggregated together because of certain similarities.
- You'll define a target number k, which refers to the number of centroids you need in the dataset.



Working of K-Means Algorithm :

We can understand the working of K-Means clustering algorithm with the help of following steps −

Step 1 − First, we need to specify the number of clusters, K, need to be generated by this algorithm.

Step 2 − Next, randomly select K data points and assign each data point to a cluster. In simple words, classify the data based on the number of data points.

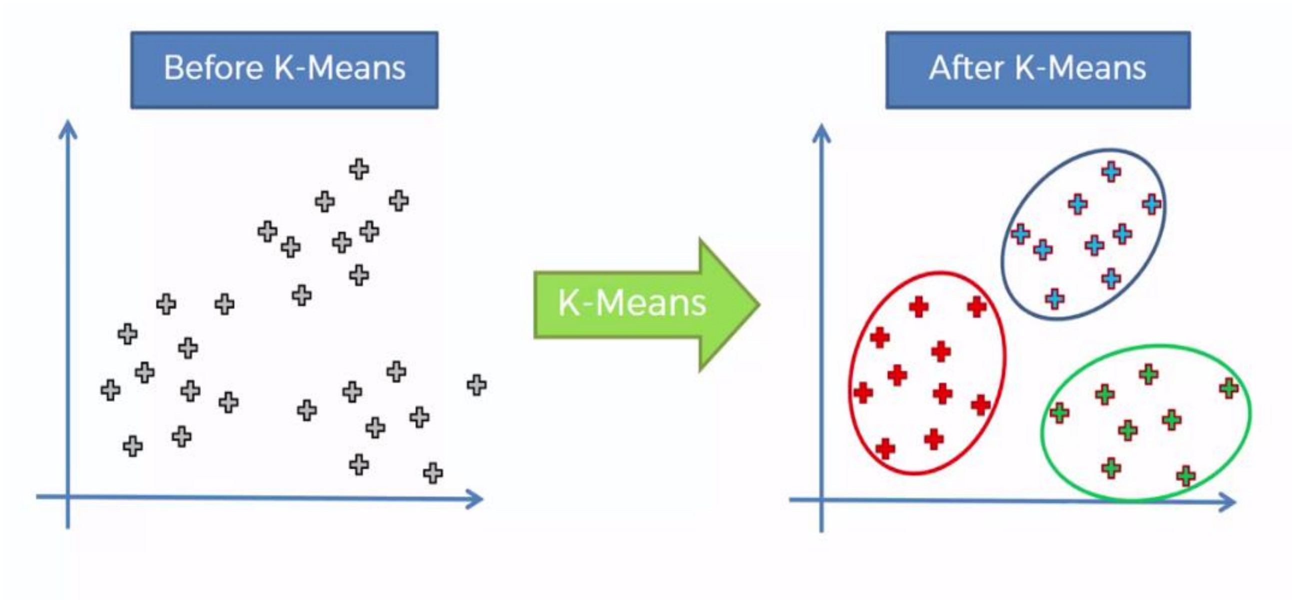
Step 3 − Now it will compute the cluster centroids.

Step 4 − Next, keep iterating the following until we find optimal centroid which is the assignment of data points to the clusters that are not changing any more

4.1 − First, the sum of squared distance between data points and centroids would be computed.

4.2 − Now, we have to assign each data point to the cluster that is closer than other cluster (centroid).

4.3 − At last compute the centroids for the clusters by taking the average of all data points of that cluster.



What is Clustering?

Imagine that you have a group of chocolates and liquorice candies. You are required to separate the two eatables. Intuitively, you are able to separate them based on their appearances. The process of segregating objects into groups based on their respective characteristics is called clustering. In clusters, the features of objects in a group are similar to other objects present in the same group.

Clustering is used in various fields like image recognition, pattern analysis, medical informatics, genomics, data compression etc. It is part of the unsupervised learning algorithm in machine learning. This is because the data-points present are not labelled and there is no explicit mapping of input and outputs. As such, based on the patterns present inside, clustering takes place.

2. Principal Component Analysis(PCA) :

- Principal Component Analysis (PCA) is a linear dimensionality reduction technique that can be utilized for extracting information from a high-dimensional space by projecting it into a lower-dimensional sub-space. It tries to preserve the essential parts that have more variation of the data and remove the non-essential parts with fewer variation.
- Dimensions are nothing but features that represent the data. For example, A 28 X 28 image has 784 picture elements (pixels) that are the dimensions or features which together represent that image.
- One important thing to note about PCA is that it is an Unsupervised dimensionality reduction technique, you can cluster the similar data points based on the feature correlation between them without any supervision (or labels), and you will learn how to achieve this practically using Python in later sections of this tutorial!
- According to Wikipedia, PCA is a statistical procedure that uses an orthogonal transformation to convert a set of observations of possibly correlated variables (entities each of which takes on various numerical values) into a set of values of linearly uncorrelated variables called principal components.
- Principal components are the key to PCA; they represent what's underneath the hood of your data. In a layman term, when the data is projected into a lower dimension (assume three dimensions) from a higher space, the three dimensions are nothing but the three Principal Components that captures (or holds) most of the variance (information) of your data.

- Principal components have both direction and magnitude. The direction represents across which principal axes the data is mostly spread out or has most variance and the magnitude signifies the amount of variance that Principal Component captures of the data when projected onto that axis. The principal components are a straight line, and the first principal component holds the most variance in the data. Each subsequent principal component is orthogonal to the last and has a lesser variance. In this way, given a set of x correlated variables over y samples you achieve a set of u uncorrelated principal components over the same y samples.

The reason you achieve uncorrelated principal components from the original features is that the correlated features contribute to the same principal component, thereby reducing the original data features into uncorrelated principal components; each representing a different set of correlated features with different amounts of variation.

Properties of Principal Component :

Technically, a principal component can be defined as a linear combination of optimally-weighted observed variables. The output of PCA are these principal components, the number of which is less than or equal to the number of original variables. Less, in case when we wish to discard or reduce the dimensions in our dataset. The PCs possess some useful properties which are listed below:

- The PCs are essentially the linear combinations of the original variables, the weights vector in this combination is actually the eigenvector found which in turn satisfies the principle of least squares.
- The PCs are orthogonal, as already discussed.
- The variation present in the PCs decrease as we move from the 1st PC to the last one, hence the importance.

Advantages of Principal Component Analysis:

1. Removes Correlated Features:

In a real-world scenario, this is very common that you get thousands of features in your dataset. You cannot run your algorithm on all the features as it will reduce the performance of your algorithm and it will not be easy to visualize that many features in any kind of graph. So, you MUST reduce the number of features in your dataset.

2. Improves Algorithm Performance:

With so many features, the performance of your algorithm will drastically degrade. PCA is a very common way to speed up your Machine Learning algorithm by getting rid of correlated variables which don't contribute in any decision making. The training time of the algorithms reduces significantly with less number of features.

So, if the input dimensions are too high, then using PCA to speed up the algorithm is a reasonable choice.

3. Reduces Overfitting:

Overfitting mainly occurs when there are too many variables in the dataset. So, PCA helps in overcoming the overfitting issue by reducing the number of features.

4. Improves Visualization: It is very hard to visualize and understand the data in high dimensions. PCA transforms a high dimensional data to low dimensional data (2 dimension) so that it can be visualized easily.

Disadvantages of Principal Component Analysis:

1. Independent variables become less interpretable:

After implementing PCA on the dataset, your original features will turn into Principal Components. Principal Components are the linear combination of your original features. Principal Components are not as readable and interpretable as original features.

2. Data standardization is must before PCA:

You must standardize your data before implementing PCA, otherwise PCA will not be able to find the optimal Principal Components.

For instance, if a feature set has data expressed in units of Kilograms, Light years, or Millions, the variance scale is huge in the training set. If PCA is applied on such a feature set, the resultant loadings for features with high variance will also be large. Hence, principal components will be biased towards features with high variance, leading to false results.

Also, for standardization, all the categorical features are required to be converted into numerical features before PCA can be applied.

3. Information Loss:

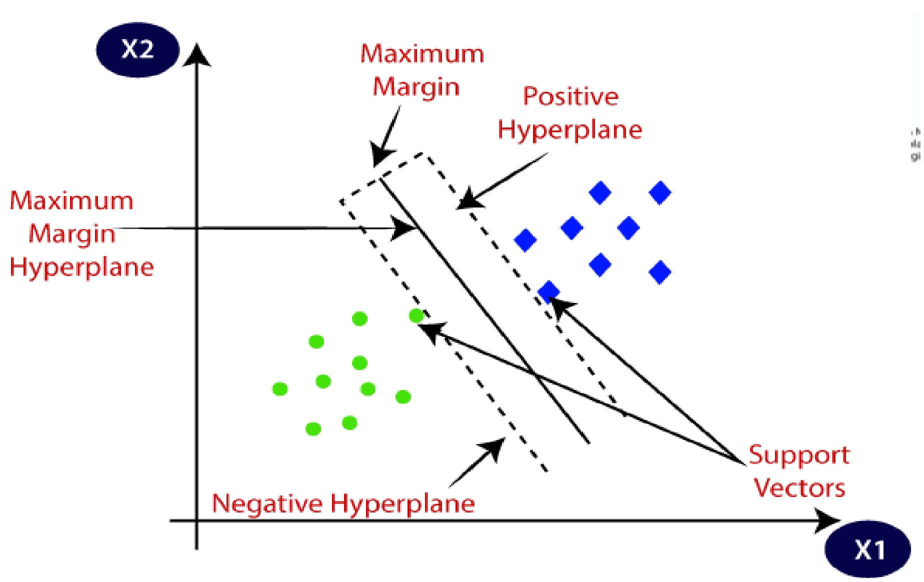
Although Principal Components try to cover maximum variance among the features in a dataset, if we don't select the number of Principal Components with care, it may miss some information as compared to the original list of features.

3. Support Vector Machine Algorithm :

Support Vector Machine or SVM is one of the most popular Supervised Learning algorithms, which is used for Classification as well as Regression problems. However, primarily, it is used for Classification problems in Machine Learning.

The goal of the SVM algorithm is to create the best line or decision boundary that can segregate n-dimensional space into classes so that we can easily put the new data point in the correct category in the future. This best decision boundary is called a hyperplane.

SVM chooses the extreme points/vectors that help in creating the hyperplane. These extreme cases are called as support vectors, and hence algorithm is termed as Support Vector Machine. Consider the below diagram in which there are two different categories that are classified using a decision boundary or hyperplane:



Types of SVM :

SVM can be of two types:

Linear SVM: Linear SVM is used for linearly separable data, which means if a dataset can be classified into two classes by using a single straight line, then such data is termed as linearly separable data, and classifier is used called as Linear SVM classifier.

Non-linear SVM: Non-Linear SVM is used for non-linearly separated data, which means if a dataset cannot be classified by using a straight line, then such data is termed as non-linear data and classifier used is called as Non-linear SVM classifier.

Hyperplane and Support Vectors in the SVM algorithm:

Hyperplane:

There can be multiple lines/decision boundaries to segregate the classes in n-dimensional space, but we need to find out the best decision boundary that helps to classify the data points. This best boundary is known as the hyperplane of SVM.

The dimensions of the hyperplane depend on the features present in the dataset, which means if there are 2 features (as shown in image), then hyperplane will be a straight line. And if there are 3 features, then hyperplane will be a 2-dimension plane.

We always create a hyperplane that has a maximum margin, which means the maximum distance between the data points.

Support Vectors:

The data points or vectors that are the closest to the hyperplane and which affect the position of the hyperplane are termed as Support Vector. Since these vectors support the hyperplane, hence called a Support vector.

SVM Kernels :

In practice, SVM algorithm is implemented with kernel that transforms an input data space into the required form. SVM uses a technique called the kernel trick in which kernel takes a low dimensional input space and transforms it into a higher dimensional space. In simple words, kernel converts non-separable problems into separable problems by adding more dimensions to it. It makes SVM more powerful, flexible and accurate. The following are some of the types of kernels used by SVM.

Linear Kernel :

It can be used as a dot product between any two observations. The formula of linear kernel is as below −

$$K(x,xi)=sum(x*xi)$$

From the above formula, we can see that the product between two vectors say x & xi is the sum of the multiplication of each pair of input values.

Polynomial Kernel:

It is more generalized form of linear kernel and distinguish curved or nonlinear input space. Following is the formula for polynomial kernel −

$$k(X,Xi)=1+sum(X*Xi)^d$$

Here d is the degree of polynomial, which we need to specify manually in the learning algorithm.

Radial Basis Function (RBF) Kernel

RBF kernel, mostly used in SVM classification, maps input space in indefinite dimensional space.

Semi-Supervised Learning :

Today’s Machine Learning algorithms can be broadly classified into three categories, Supervised Learning, Unsupervised Learning and Reinforcement Learning. Casting Reinforced Learning aside, the primary two categories of Machine Learning problems are Supervised and Unsupervised Learning. The basic difference between the two is that Supervised Learning datasets have an output label associated with each tuple while Unsupervised Learning datasets do not.

The most basic disadvantage of any Supervised Learning algorithm is that the dataset has to be hand-labeled either by a Machine Learning Engineer or a Data Scientist. This is a very costly process, especially when dealing with large volumes of data. The most basic disadvantage of any Unsupervised Learning is that it’s application spectrum is limited.

To counter these disadvantages, the concept of Semi-Supervised Learning was introduced. In this type of learning, the algorithm is trained upon a combination of labeled and unlabeled data. Typically, this combination will contain a very small amount of labeled data and a very large amount of unlabeled data. The basic procedure involved is that first, the programmer will cluster similar data using an unsupervised learning algorithm and then use the existing labeled data to label the rest of the unlabeled data. The typical use cases of such type of algorithm have a common property among them – The acquisition of unlabeled data is relatively cheap while labeling the said data is very expensive.

Most of the time, we need labeled data to do supervised machine learning. I particular, we use it to predict the label of each data point with the model. Since the data tells us what the label should be, we can calculate the difference between the prediction and the label, and then minimize that difference.

A Semi-Supervised algorithm assumes the following about the data –

Continuity Assumption: The algorithm assumes that the points which are closer to each other are more likely to have the same output label.

Cluster Assumption: The data can be divided into discrete clusters and points in the same cluster are more likely to share an output label.

Manifold Assumption: The data lie approximately on a manifold of much lower dimension than the input space. This assumption allows the use of distances and densities which are defined on a manifold.

Practical applications of Semi-Supervised Learning –

Speech Analysis: Since labeling of audio files is a very intensive task, Semi-Supervised learning is a very natural approach to solve this problem.

Internet Content Classification: Labeling each webpage is an impractical and unfeasible process and thus uses Semi-Supervised learning algorithms. Even the Google search algorithm uses a variant of Semi-Supervised learning to rank the relevance of a webpage for a given query.

Protein Sequence Classification: Since DNA strands are typically very large in size, the rise of Semi-Supervised learning has been imminent in this field.

Reinforcement Learning:

Like traditional types of data analysis, here, the algorithm discovers data through a process of trial and error and then decides what action results in higher rewards. Three major components make up reinforcement learning: the agent, the environment, and the actions. The agent is the learner or decision-maker, the environment includes everything that the agent interacts with, and the actions are what the agent does.

Reinforcement learning occurs when the agent chooses actions that maximize the expected reward over a given time. This is easiest to achieve when the agent is working within a sound policy framework.

You will understand why Machine Learning is important in the next section of What is Machine Learning article. Also, check out the Simplilearn's video on "What is Machine Learning" curated by our industry experts.

Main points in Reinforcement learning –

- Input: The input should be an initial state from which the model will start
- Output: There are many possible output as there are variety of solution to a particular problem
- Training: The training is based upon the input, The model will return a state and the user will decide to reward or punish the model based on its output.
- The model keeps continues to learn.
- The best solution is decided based on the maximum reward.

New Challenges :

As you can imagine, this kind of problem creates a whole new set of challenges. One of the biggest issues is just the size of the state-space itself. Many reinforcement learning problems have state-spaces that contain billions, trillions, or even an infinite number of states. These massive state-spaces typically occur because of

1) very complex states with a large number of variables,

2) states that involve randomness so a single action could lead to a number of different outcomes, or both.

Types of Reinforcement:

There are two types of Reinforcement:

Positive –

Positive Reinforcement is defined as when an event, occurs due to a particular behavior, increases the strength and the frequency of the behavior. In other words, it has a positive effect on behavior.

Advantages of reinforcement learning are:

- Maximizes Performance
- Sustain Change for a long period of time

Disadvantages of reinforcement learning:

- Too much Reinforcement can lead to overload of states which can diminish the results

Negative –

Negative Reinforcement is defined as strengthening of a behavior because a negative condition is stopped or avoided.

Advantages of reinforcement learning:

- Increases Behavior
- Provide defiance to minimum standard of performance

Disadvantages of reinforcement learning:

- It Only provides enough to meet up the minimum behavior

Various Practical applications of Reinforcement Learning –

- RL can be used in robotics for industrial automation.
- RL can be used in machine learning and data processing
- RL can be used to create training systems that provide custom instruction and materials according to the requirement of students.

RL can be used in large environments in the following situations:

1. A model of the environment is known, but an analytic solution is not available;
2. Only a simulation model of the environment is given (the subject of simulation-based optimization)
3. The only way to collect information about the environment is to interact with it.